THE USE OF THE RECOGNITION HEURISTIC AS AN INVESTMENT STRATEGY IN EUROPEAN STOCK MARKETS

By

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Biographical note

Carlos Pereira was born in Braga, Portugal in 21st March, 1990. Academically, he graduated in Economics from University of Minho in 2011. During this period he performed a semester of his studies at Universidad Autonoma de Madrid under the Erasmus program. In 2013 he joined the Master in Finance from University of Porto School of Economics and Management, which he is currently pursuing its accomplishment. Professionally, he performed an internship in IBM at the accounts payable department in 2012. In the same year he joint EditValue as intern consultant. In 2014 he started a new experience in adidas Group in accounts payable department, leaving the company in August 2015 to join the Assurance team from Ernest & Young, position that currently holds.

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Abstract

Theoretically, it is believed that individuals are fully rational and always take the optimal decision when facing an investment opportunity. Nevertheless, that way of thinking may not be very realistic when dealing with real word situations, as usually individuals may face constrains that lead to limited rationality, such as limited time to take decisions or lack of knowledge. In these situations, heuristics are useful to take some shortcuts in order to decide faster and with fewer resources, even if that leads to suboptimal choices.

The concept of Recognition Heuristics has its origin on the psychology and states that an individual, when facing the challenge to choose between two objects and he is familiar with only one of the objects, the individual would always choose the object that he is familiar with. When applied to financial markets, it is supposed that investors may acquire only the stocks that they are aware of, inflating the price of the most recognized stocks.

In this master dissertation it was performed a survey and used Google Trends to study the profitability of the most recognized stocks on Europe against the market.

Based on the survey performed, it was concluded that the Recognition Heuristic effect portfolio yielded poorer returns than the market portfolio. In contrast, from the data collected from Google Trends it was found weak evidence that strong increases in companies monthly search volume may lead to abnormal returns in the following month. Nevertheless, the investment strategy applied does not account for transaction costs, which may jeopardize its profitability, given the fact that it is necessary to revise the portfolio in a monthly basis.

Key-words: Recognition Heuristic, Financial Market, Eurozone, Behavioural Finance, Investment Decisions, Stock Returns.

JEL codes: G11, G12

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1. Introduction

The concept of Recognition Heuristics has its origin on the psychology and intends to be a fast and frugal way of thinking to take decisions on a bounded rationality scenario.

In theory, it is recognized that individuals are fully rational and always take the optimal decision when facing a problem. However, that way of thinking, despite of being defended by several authors, may not be very realistic when dealing with real word situations, as usually individuals face certain conditions that may lead to limited rationally, such as limited time to take the decision or lack of knowledge. So, heuristics are useful to take some shortcuts in order to decide faster and with fewer resources, even if that leads to suboptimal decisions. The recognition heuristics state that an individual, when facing the challenge to choose between two objects and he is familiar with only one of the objects, the individual would always choose the object that he is familiar with.

Introducing this concept on financial markets, it would be interested to study if the most recognized stocks provide abnormal returns on a consistent basis, as the result of individuals choosing to buy the stocks that they are most familiar with. This would contribute to the discussion of the Efficient Market Hypothesis (Fama, 1970) that states that no investment strategy can beat the market consistently. Also, on the last years the behavioural approach has emerged and states that financial markets are made of individuals and those often may take irrational decisions, which may lead to inefficiencies in the financial markets.

The first authors to link recognition heuristics with financial markets were Borges *et al.* (1999) and they found some evidence that recognized stocks may produce greater returns than a buy and hold strategy of the market portfolio. However, they only used a time horizon of 6 months and experienced an extremely bull market. Thus, they could not prove the consistency of this strategy. Thereafter, Boyd (2001) tried to replicate this strategy and concluded that recognition heuristics may produce abnormal returns only during bull markets. When facing other market conditions, the strategy produced poor results. The last authors to discuss this topic were Andersson and Rakow (2007) concluding that investor's "ignorance" would not be a valuable asset when taking investment decisions, nevertheless Recognition Heuristics strategies would yield better returns in bear markets than in rising ones.

So, these three studies reflect the lack of consensus about this topic, which suggests that further discussion on this topic may be a relevant contribution to science. The main objective of this dissertation is to study if recognized stocks produce abnormal returns on a consistent basis. In other words, infer if a portfolio constructed of the most recognized stocks of a given economy may consistently beat the market portfolio.

Following the same approach as per Borges *et al.* (1999), Boyd (2001) and Andersson and Rakow (2007), the only three studies that cover the recognition heuristic when applied to financial markets, a survey was performed in order to infer which stocks from the STOXX® Europe 50 are most recognized. The survey was performed to 272 participants and two portfolios were constructed: the recognized portfolio (which includes the stocks issued by those firms that were recognized by more than 90% of the subjects) and the unrecognized portfolio (which contains the stocks issued by those firms that were recognized only by less than 10% of the subjects). The performance of each portfolio was compared with the market portfolio in order to infer if the Recognition Heuristic strategy yields better returns than the market.

In the five month period following the portfolio formation the market portfolio yielded more 5.45 percentage points than the recognized portfolio and more 7.11 p.p. than the unrecognized portfolio. All the three portfolios presented similar levels of risk, captured by the daily standard deviation of returns and portfolio's Beta. Therefore, it is possible to infer that investing in the European market based on individual's "ignorance" do not produce any excess of return.

In order to complement the dissertation an additional methodology was adopted. The introduction of Google Trends enable everyone to access the keyword search volume variation across time. The existence of this tool was considered as relevant to study Recognition Heuristic, as search volume may be used as a proxy for investor recognition. In other words, it is expected that the most recognized companies present higher investor's attention on the Web than the companies less recognized. The data provided by Google Trends is not given in absolute terms, but as a value relative to the total number of searches on Google during a given time interval. Therefore, for each keyword analysed this relative value is normalized to the interval between 0 and 100, where the 100 represent the period in which the search volume was the highest on the time interval under analysis and 0 is obtained when the search volume does not reach a designated search volume threshold (Banks *et al.*, 2011). This data transformation inhibits us from comparing between keywords absolute search volume, nevertheless we still can infer individually the behaviour of each company popularity across time.

As per Banks *et al.* (2011) three equal sized portfolios were constructed each month: one composed by the companies which search volume increased the most, another with the companies that the search volume most decreased and one with the remaining companies, which are the ones that verified small changes in search volume. Thereafter, two investment strategies were tested during the period under analysis relying on the Recognition Heuristic. In order to verify the performance of each investment strategy, the returns obtained were regressed against the risk factors included in three relevant market models: the CAPM from Sharpe (1964), the Three-factor model from Fama and French (1993) and the Carhart (1997) Four-factor model. The Jensen's alpha[1] was estimated to infer if the designed investment strategies could beat the market on a consistent basis.

The results showed that following a strategy based on the Recognition Heuristic principles it is possible to yield weak, but statistically insignificant abnormal returns on a consistent basis. Nevertheless, the investment strategy would imply to modify the portfolio on a monthly basis, which can lead to high transaction costs that could absorb the strategy profitability.

This master dissertation is organized in five chapters. The second section presents the literature review with the relevant authors, the third section discusses the methodologies used and the fourth section presents and analyses the results obtained in this master dissertation. Lastly, in the fifth chapter we present the main conclusions of this Master thesis.

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[1] Jensen's alpha may be used to measure the abnormal return of a security or portfolio over the theoretical expected return (Jensen, 1968).

2. Literature Review

This chapter is intended to comprehensively analyse the discussion of Recognition Heuristics within the literature, since the very beginning until nowadays.

In order to present the ideas in a more understandable manner, it will be presented firstly the concept of Recognition Heuristic and its origin within the psychology field. Only thereafter, it will be presented the application of Recognition Heuristic to financial markets and the relevant author in this topic.

2.1. Recognition Heuristic

The concept of recognition heuristic was introduced by Goldstein & Gigerenzer (1999, 2002) and its pretended to "exploit the vast and efficient capacity of recognition to make inferences about unknown aspects of the world" (Goldstein and Gigerenzer, 1999, p. 4).

In order to understand what recognition heuristic is please "consider the task of inferring which of two objects has a higher value on some criterion (e.g. which is faster, higher, stronger). The recognition heuristic for such task is simply stated: if one of the two objects is recognized and the other is not, then infer that the recognized object has the higher value" (Goldstein and Gigerenzer, 1999, p. 41). For instance, someone is asked which Portuguese city has higher population, Porto or Braga? If that individual has heard about Porto before and not about Braga, he could correctly infer that Porto has higher population than Braga.

The heuristic is non-compensatory, which means that no other information aside from recognition is taken into account in the judgment (Goldstein and Gigerenzer, 1999). This feature is also known as the *less-is-more* effect. In order to evidence this feature, Goldstein and Gigerenzer (2002) performed a test where they asked about a dozen Americans and Germans which city has higher population between San Diego or San Antonio. About two thirds of the Americans replied correctly San Diego, whilst all the German (with significantly less knowledge) answered correctly to the question. The impressive result obtained on the German group was due to a simple fact: all the

German tested have heard about San Diego before and about half of them did not recognized San Antonio. This process is counterintuitive as it is defended that people with less knowledge can decide better than people with a broader knowledge about the topic.

The term "recognition" has been used in many contexts, so it is crucial to explain the meaning of the concepts used by these authors. According to Goldstein & Gigerenzer (1999, 2002) we may divide the objects in observation into three different degrees of recognition. In order to understand these differences please pretend that Tom step onto a bus. The passengers that he is sure he has never seen before represent the unrecognized objects. Probably, Tom will also face some people that he knows, however he cannot identify or recall anything about (there's a famous Irish expression to this: *to tartle*). These individuals that make Tom *tartle* represent the mere recognition category. Lastly, Tom may find some people that he can recognize and also identify additional information (e.g. what their profession is). Those persons represent recognition plus further knowledge category.

Of course, the recognition heuristic cannot be applied in every situation or even make correct inferences using it. Recognition heuristic is *domain-specific*, so it only works in environments where recognition is correlated with the criterion. Pachur *et al.* (2011, p. 1) stated that "the exploitable relation between subjective recognition and some (not directly accessible) criterion results from a process by which the criterion influences object recognition through mediators, such as mentions in newspapers, on the Internet, on radio, on television, or by word of mouth. Specifically, objects with high criterion values tend to be mentioned more frequently in the news, frequent mentions increase the likelihood that their name will be recognized, and as a consequence, recognition becomes correlated with high criterion values". For instance, we may consider company size as example for this feature. This means, that bigger companies have more chances to be quoted in newspapers than smaller companies, increasing the knowledge from the population about the bigger companies.

According to Goldstein and Gigerenzer (1999, p. 44) "ignorance is beneficial if it is correlated with what one wishes to infer". For instance, because city size is positively associated with recognition, the Recognition Heuristic would predict that recognized cities would be judged as larger than unrecognized cities.

Moreover, please bear in mind that recognition heuristics "does not apply to situations in which people already have conclusive criterion knowledge about the objects, which allows a response to be deduced" Pachur *et al.* (2011, p. 2).

Recognition may be also easily misunderstood with completely different notions such as availability (Tversky and Kahneman, 1974) and familiarity (Griggs and Cox, 1982). As stated by Goldstein and Gigerenzer (2002, p. 77) "the availability heuristic is based on recall, not recognition. People recognize far more items than they can recall. Availability is a graded distinction among items in memory and it is measured by the order or speed with which they come to mind or the number of instances of categories one can generate. The term familiarity is typically used in the literature to denote the degree of knowledge (or amount of experience) a person has of a task or object. The recognition heuristic, in contrast, treats recognition as a binary, all-or-none distinction; further knowledge is irrelevant" Goldstein and Gigerenzer (2002, p. 77).

Pachur *et al.* (2011) mentioned the collective recognition (i.e. the proportion of people in some population that recognize the object) that several authors use as method of their analysis, as not being direct implementations of the recognition heuristic, which models the use of individual recognition. Nevertheless, some caution is required to this type of analysis as "the cognitive processes involved would be different from the recognition heuristic (e.g., including recall of the collective recognition rates or their estimation in other ways, such as by the number of people observed to have chosen some option)" Pachur *et al.* (2011, p. 4).

2.2. Recognition Heuristic applied to financial markets:

Merton (1987) was the first economist to point out the concept of recognition and to presume that investor attention may be relevant to stock pricing. The "investor recognition hypothesis" defends that in informationally incomplete markets, investors are not aware of all securities available for investment. Therefore, stocks with lower investor recognition need to offer higher returns to compensate their investors for being long in securities with less information available and less media coverage. Consequently, in theory stocks with higher investor's recognition earn lower returns than stocks with lower visibility (Merton, 1987). Indeed, Fang and Peress (2009) empirically found a stable, negative relationship between media coverage and required rate of return and attributed this finding to the effect highlighted by Merton (1987).

Borges *et al.* (1999) were the first authors to implement the recognition heuristic on building portfolio strategies. The idea was to take advantage of a fast and frugal decision process to see if with less knowledge it could be possible to form a better portfolio than an investor would if it had access to tons of information and resources. As the authors state "the tools and information professional investment firms use for investment decisions are far beyond the ordinary person's reach" Borges *et al.* (1999, p. 59).

The idea was to take advantage of recognition heuristics and form an investment portfolio relying only on one piece of information: company name recognition. No information would be necessary (e.g. firms fundamentals, price, financial indicators, etc.). As per Borges *et al.* (1999, p. 59) "the only thing one needs is a beneficial degree of ignorance".

Financial markets are quite complex and few investors were able to consistently beat the market consistently over the years. The famous concept of Efficient Market Hypothesis (EMH) introduced by Fama (1970) and defend by several other authors, such as Lucas (1981), asserts that investors are unboundedly rational and financial markets are informationally efficient, which leads to the conclusion that no one can consistently achieve higher returns than the market on a risk-adjusted basis, given the information available at the time the investment is made. Furthermore, the widespread and most used Capital Asset Pricing Model (CAPM) by Sharpe (1964) incorporate itself the assumptions of rationality and information efficiency taken by EMH.

Therefore, it is quite optimistic to propose a very simple strategy as the one that it could yield abnormal returns consistently to the most ignorant investors. This strategy relies on behavioural finance principles of bounded rational brought by modern finance, with authors such as Debondt and Thaler (1985), Arthur (1996), Shleifer (2000), Akerlof and Shiller (2010) and Statman (2014).

Despite the shift in academic research, the performance of professional managed investment funds show evidence of how difficult is to beat the market in the long run. At a glance, the worldwide community is quite sceptical with the results that Recognition Heuristic may bring to regular investors.

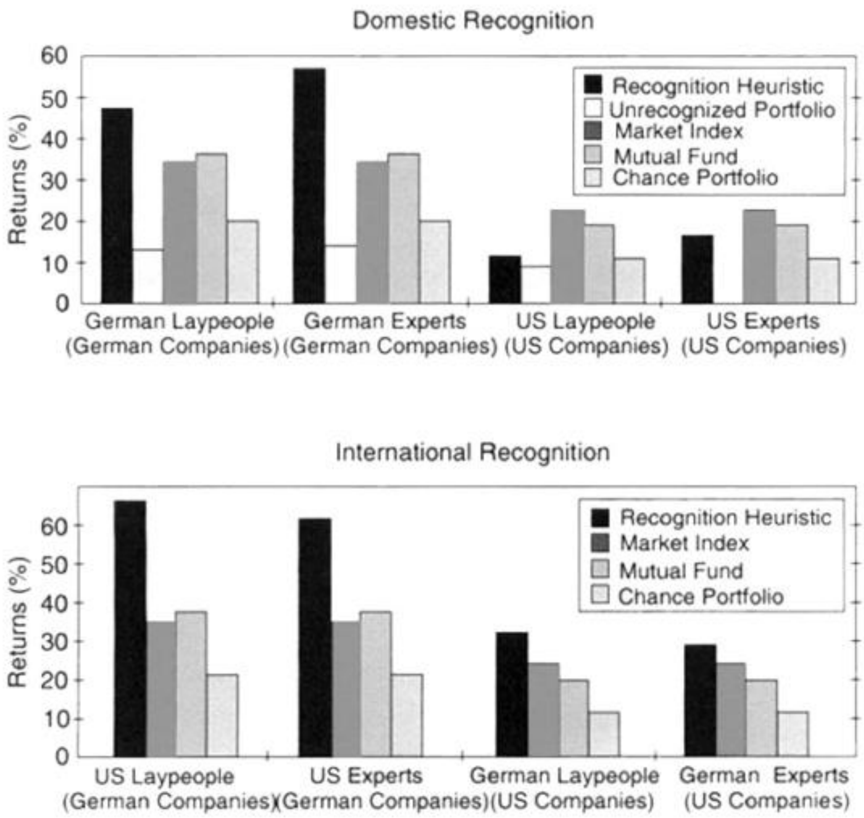
Recognition Heuristic from Goldstein and Gigerenzer (1999, 2002) dictates that one individual should choose only the stocks he recognizes. However, Borges *et al.* (1999) used a derivation of recognition heuristic called "collective recognition" (Pachur *et al.*, 2011). At Borges *et al.* (1999) several portfolios of stocks were constructed using name recognition of 500 American stocks and 298 German stocks (companies listed on S&P500 and Dax 30 were included) by: American laypeople, American experts, German laypeople and German experts, where a total of 480 people were surveyed.

Based on the survey, eight recognition-based portfolios were built. The "domestic recognition" portfolios were constructed with the stocks that more than 90% of the participants recognized for their country. The "international recognition" resulted on the portfolios with the 10 stocks most recognized from the foreign country.

In Figure 2.2.1 it can be observed the results obtained on the six-month period after the survey. From its analysis, it is possible to infer that domestic recognition outperformed by a large margin the other benchmarks only for German laypeople and experts. In US, the domestic recognition performed below the market index and also the mutual fund industry. However, the international recognition portfolio obtained results quite impressive. For instance, US laypeople recognition's portfolio beat the market by 23%. The aggregate results were very positive to recognition heuristics as in six out of eight tests it has beaten the market, often by a large margin.

According to Borges *et al.* (1999, p. 71) "the superiority of international over domestic recognition and the superiority of laypeople over experts in stock picking supports the notion that a certain degree of ignorance can be a virtue".

Figure 2.2.1 Performance of recognition heuristic for domestic and international recognition



Source: Borges et al. (1999)

Some speculation is given on the reasons why Recognition Heuristic performed so well in the stock market. First, following the findings of Buzzel *et al.* (1975) and Ramanujam & Venkatraman (1984), it was found evidence of positive correlation between market share and profitability. Therefore, "companies with the dominant market share are most likely to become both recognized and profitable. One more reason for good performance of recognition heuristic is the link of profitability is core competence. For instance, "Honda is generally portrayed as possessing core competence in engines, which are featured in a variety of products, such as cars, lawn mowers, boat engines and power generators" (Borges *et al.*, 1999, p. 71) and seems to be some evidence that core competence is linked to above-average performance (Prahalad & Hamel, 1990 and Hamel & Prahalad, 1994).

Lastly, company name has value and it is important information for investors. Signal of that is the “countless court cases over corporate name ownership” (Borges *et al.*, 1999, p. 71).

The above-average returns presented by Borges *et al.* (1999) may also be a result of the extremely bull market experienced during the period of the study. According to Borges *et al.* (1999, p. 71) “One explanation for the recognition heuristic's good performance is that it is picking “big” firms, which are known to do well in up markets. This hypothesis can be tested in a down market, where big firms generally do more poorly than the market indices. If recognized stocks perform above big firms in upswings, and do not suffer as much in downturns, then we will have evidence distinguishing recognition effects from big-firm effects”.

The claiming for further investigation under different market conditions was fulfilled by Boyd (2001). This author attempted to replicate the same experiment as Borges *et al.* (1999) under a bear market to test if the recognition heuristic still produces good results with this conditions.

The method used was the same, surveying a group of students of business school in U.S. and another group of non-business courses, performing an overall of 184 participants. A list of 111 stocks randomly extracted from the S&P500 was given to them in order to infer the most recognized stocks.

From the participants responses, a single high-recognition test portfolio was constructed for both group (business and non-business students) using the stocks recognized by more than 90% of the participants. The portfolio comprised equal dollar weightings for the twenty three stocks in order to ensure that each stock will be equally represented in the study. The market portfolio was considered as the one composed by the 111 stocks used for the survey, also equal dollar weighted.

During the following six month period, the market portfolio lost 4.54% and the highly recognized stocks portfolio registered a loss of an expressive 14.75%. An additional test was also performed out of curiosity. A portfolio was built containing the twenty least recognized companies by the combined participant groups. The results were quite surprising. The portfolio yielded a gain of 16.27% during the same six month period.

According to Boyd (2001, p. 155) “a high degree of company name recognition can lead to disappointing investment results in a down market, and it can also be beat by pure ignorance”. Nevertheless, Boyd (2001) provided some guidance for further research. According to him, it could be valuable test the performance of the stocks that people only recognize the name and do not know any other information about the company, such as financials, and compare its performance with unrecognized portfolio.

Another similar study was performed by Andersson and Rakow (2007) attempting to replicate the findings of Borges *et al.* (1999). Therefore, they performed four different surveys. In the first, 53 UK psychology students provided recognition data for the 30 companies listed on the MIB30 index, the representative of Italian stock market. The second study intended to survey 52 UK psychology students and 15 Swedish business students about recognition for UK, Swedish and Italian stock exchanges. The authors extracted a list of 15 companies from each market index (UK FTSE 100, Swedish Stockholmbörsen and Italian Mib30). The shares selected were the ones with the highest volume for each stock index. In the third study, 70 UK psychology students, 78 Austrian business students and 36 Swedish business students provided recognition data for Austrian, Swedish and German stocks. On the survey was a list of 48 stocks, of which nine, sixteen and 23 were randomly extracted respectively from Austrian prime list, the Swedish A-List and the German prime standard. Finally, on the fourth study 15 Swedish business students provided recognition data for UK, Swedish and Italian stocks. Here the stocks under analysis were the same 45 as on the study 2, excepting one that ceased to trade meanwhile (Andersson and Rakow, 2007).

Andersson and Rakow (2007) failed to achieve the same results and concluded that “intermediate levels of recognition might yield better (or worse) returns than both low and high levels of recognition also failed to show a consistent or predictable pattern” (Andersson and Rakow, 2007, p. 36). Therefore, “ignorance” has no special advantage or disadvantage over sophisticated knowledge.

In contrast with the findings of Borges *et al.* (1999), “the recognition heuristic tended to fare well in falling markets and perform poorly in rising ones” (Andersson and Rakow, 2007, p. 36).

3. Methodology

The study of the impact of recognition heuristic in stock market returns requires that firstly the recognized stocks are identified out of the unrecognized stocks.

In order to proceed with this study about the existence of Recognition Heuristic in stock market returns it will be used two different approaches. This way, it will be intended to study the phenomena into different scenarios, so the validity of the dissertation and its conclusions could be more effective.

As Borges *et al.* (1999), Boyd (2001) and Andersson and Rakow (2007), a survey will be performed to infer which stocks are the most recognized from the STOXX® Europe 50 index. The index is composed by fifty leading Blue-chip company on the European region providing a representation of sector leaders in this market.

In order to complement this dissertation an additional methodology was adopted. Google Trends will be used to access keyword internet search volume variation across time, which it will be used as proxy for investor recognition. The existence of this tool was considered as relevant to study Recognition Heuristic, as Internet search volume may be used as a proxy for investor recognition. Subsequently, two investment strategies will be design accordingly to the Recognition Heuristics principles and their profitability will be compared to the market return.

In other words, it is expected that the most recognized companies present higher investor's attention on the Web than the companies less recognized. The data provided by Google Trends is not given in absolute terms, but as a value relative to the total number of searches on Google during a given time interval. In other words, for each keyword analysed this relative value is normalized to the interval between 0 and 100, where the 100 represent the period in which the search volume was the highest on the time interval under analysis and 0 is obtained when the search volume does not reach a designated search volume threshold (Banks *et al.*, 2011) . This data transformation performed by Google inhibits us from comparing between keywords absolute search volume, nevertheless we still can infer individually the behaviour of each company popularity across time.

3.1. Survey

Aligned with the methodology followed by Borges *et al.* (1999), Boyd (2001) and Andersson and Rakow (2007) the survey is composed with three type of questions.

The first two questions have merely the objective of collecting information about the participants' nationality and age bracket. Those are followed by three questions that identify the participant's level of expertise on financial markets. Here the participant has to describe his level of education and if belongs to the field of business/finance or not. Additionally, it is requested to answer the frequency of investments performed on financial markets (such as stocks, mutual funds and futures). Closing this group of questions, the participant should describe how often he seeks to read/watch financial news. The last question pursues to discover which stocks are most well-known from the list presented. At this point, the participant is presented with a list with the company names that compose the index STOXX® Europe 50 from which is asked to identify the names recognized. The company names on the list were replicated from Thomson Reuters Datastream to avoid arbitrariness and ensure that participants are presented with a standardized name selection process.

The survey was presented to participants through Google Forms and it was available in two languages: Portuguese and English. The participant has the option to choose the most suitable version.

In order to distribute the survey on a more effective and faster method, it was decided that the webpage links for the survey should be provided through social networks, such as Facebook and LinkedIn. Additionally, it was asked the cooperation of colleagues to spread the survey's through their contacts.

As per Borges *et al.* (1999), Boyd (2001), it was constructed a portfolio with the stocks recognized by more than 90% of the participants. Additionally, and similarly with the previous studies, it was also constructed a portfolio with the stocks which company name was recognized by less than 10% of the participants. The construction of the portfolios obey to the equally weight rule, where each company contributes equally for the portfolio's performance. These two portfolios were then pledge against the market portfolio in order to compare the performance of both strategies.

Please recall that (Pachur *et al.*, 2011) mentions that collective recognition is a variant of recognition heuristic and may agglomerate other effects beyond recognition. Having said that, it was intended to eliminate this type of biases recurring to the survey. For that, individual portfolios were constructed with the recognized stocks for each participant. The portfolio was then compared with the returned from the market portfolio. In order to avoid very similar returns to the market portfolio due to composition, it will be removed from this analysis the individuals who recognized more than 90% of the companies, i.e. more than 45 companies. This kind of approach will make possible to analyse the return obtained per participant under the recognition heuristic principle and aggregate the results per participant's degree of expertise.

Each portfolio will be valued following the equally weighted rule, so each stock may have exactly the same preponderance over the recognized portfolio. The survey was implemented during December and the portfolio will be constructed using opening price on Thomson Reuters Datastream of 5^{th} January 2015. The holding period consider was 5 months, being the closing price the 5^{th} May chosen for liquidating the portfolios.

The return of each portfolio was compared with the STOXX® Europe 50 return and it will be searched for evidence of correlation between excess of return per each degree of expertise.

3.2. Google Trends as proxy for investor's recognition

The "investor recognition hypothesis" defends that in a market with incomplete information, investors are not aware of all securities available for investment. Consequently, stocks with lower investor recognition provide higher returns in order to compensate investors for idiosyncratic risk that cannot be diversified (Merton, 1987). Moreover, given that Google search volume adequately proxies for investor attention and assuming that financial markets are characterized by incomplete information, it would be expected a negative and persistent interdependence between changes in search volume and future returns. Following this idea, Fang and Peress (2009) found a stable negative relationship between coverage and required rate of return and attributed this finding to the effect of investor attention defended by Merton (1987). On the other hand, Barber and Odean (2008) defend that investors are able to choose from a large set of stocks when they want to buy, nevertheless they only have a limited choice when selling securities. Subsequently, the increment of stock attraction should affect more the buying side than selling, mostly by particular and uninformed investors. As per the conclusions of Barber and Odean (2008), Da *et al.* (2011), who also measure attention using Google search volume, empirically observed that positive changes in the number of Internet queries push up prices temporarily.

Measuring investor recognition is not an easy task. For instance, Fang and Peress (2009) captured the attention attracted by firms using as proxy the number of times that the company name appears on the newspaper. Unfortunately, “there is no reliable information as to the extent to which readers of a newspaper pay attention to the mention of a company in its pages. Other measures of investor attention, such as analyst coverage, institutional holdings, or advertisement expenditures, suffer from similar shortcomings” (Fang and Peress, 2009, p. 240).

The first authors to suggest to use the search volume to access firm’s recognition was Da *et al.* (2011). Nowadays, the number of search queries as an indicator of people interest has great appeal. The internet connection is well spread across the globe and practically every investor is able to access companies’ information through it. As evidence of that, virtually every listed company has a website and uses it to disclose valuable information for investors (e.g. news, annual reports, etc.). Also, search volume seems appropriate, since an Internet user will only actively “Google” a specific keyword if he or she is interested in the object underlying the search term. Ultimately, the information about query volumes is freely available on Google Trends which makes it more appealing to be used.

In order to obtain the search volume for each company Da *et al.* (2011) used the ticker symbol for the underlying company. Nevertheless, Bank *et al.* (2011) opted to use the ordinary firm names, as they believed that this method captures the extent of attention the firm is receiving from much broader, and potentially relevant audience. The average Internet user is expected to search for a firm on Google by its own name and it is not likely to use the ISIN (International Securities Identification Numbers), WKN (German securities identification code), or other technical stock symbols.

Bank *et al.* (2011) used Google Trends to access search volume of firm names as a proxy for investor attention and study the implications for trading activity, liquidity and returns for German stocks. They concluded that "search volume is indeed a powerful measure of investor recognition. In particular, an increase in Internet search volume is related to higher trading activity, improved stock liquidity, and leads to higher future returns in the short-run" (Bank *et al.*, 2011, p. 240).

In this study, it was used the same approach as Bank *et al.* (2011), where the ordinary company names functioned as proxy to access firm's recognition level. Furthermore, Google Trends has the option to specify which the environment for which keyword to be used is. For instance, if we insert ALLIANZ on the tool, we have the option to specify that we want to obtain the search volume for the searches that are related to the financial services company. This option was used to empower the effectiveness of the search, in order to select the searches that concern the company name and reject the searches that may be related with other topics. This feature is especially important in keywords as Orange, for instance, which enable us to eliminate searches related to that colour or fruit.

The purpose of this analysis is to infer if increments in Google searches may lead to higher returns on the following month for the related stock.

As Google is the search engine most used worldwide, the choice of Google Trends was obvious to proceed with our study. The only downside is that the search volume of a specific keyword is not given in absolute terms, but as a value relative to the total number of searches on Google during a given time interval. Therefore, for each keyword analysed this relative value is normalized to the interval between 0 and 100, where the 100 represent the period in which the search volume was the highest on the time interval under analysis and 0 is obtained when the search volume does not reach a designated search volume threshold (Bank *et al.*, 2011). This data transformation performed by Google inhibits us from comparing between keywords absolute search volume, nevertheless we still can infer individually the behaviour of each company popularity across time.

Each stock composing the STOXX® All Europe 50 will be accessed its search index value given by Google Trends and the time interval for the analysis will be comprised since January 2004 to April 2015. The time interval was chosen based on the data availability for Google Trends, as January 2004 was the starting point for Google registering the search volume. Also, having slightly more than 10 years of data seems to be adequate to measure the correlation between stocks increase in stock returns with previous increments of company popularity. To perform this analysis monthly data will be used.

Furthermore, as per Bank *et al.* (2011), it were only included in this study companies where the search volume is provided for more than five months. From those, it were dropped all the companies where the search volume equals zero two or more consecutive months. Accordingly to Bank *et al.* (2011, p. 243) "these observations, on the one hand, they do not provide any analysable within variation for our investigation and, on the other hand, they should distort the portfolio formation approach". Following this approach, only the data related to Anheuser-Busch Inbev, Lloyds Banking Group and Glencore PLC was left apart from the study.

Following the methodology adopted by Bank *et al.* (2011), the monthly data collected in Google Trends will be sorted into three quantiles of equal size each month accordingly to the change in search value. From there, every month three different portfolios will be constructed for investing in the very next month: one composing the 33% of companies with highest increase in search volume, another with the 33% of companies with highest decrease in search volume and the remaining with the 33% of companies with smallest variation in search volume. The return of each portfolio will be computed as the average return for the stocks held by the portfolio in the following month. Thereafter, the time series of portfolio returns of the month after the portfolio formation are regressed on recognized risk factors by employing three different market models: the CAPM by Sharpe (1964), the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model (Bank *et al.*, 2011). The Equation 3.3.4 (Barber and Odean, 2000) represents the CAPM model, where the R_{ISt} = the monthly return obtained with the investment strategy, R_{ft} = the monthly return on risk-free rate, α_i = CAPM intercept (Jensen's alpha), β_i = the market beta, $R_{mt} - \mathrm{R}_{ft}$ = the market premium and ε_i = the regression error term. Moreover, to estimate the Fama and French (1993) three-factor model, it will be added two more risk-factors, the market capitalization SMB_t and the book to market HML in Equation 3.3.5 (Barber and Odean, 2000). The Carhart (1997) four-factor model adds the momentum variable WML and may be found in Equation (3.3.6).

$$\mathrm{R}_{ISt} - \mathrm{R}_{ft} = \alpha_i + \beta_i(R_{mt} - \mathrm{R}_{ft}) + \varepsilon_i \qquad (3.2.1)$$

$$\mathrm{R}_{ISt} - \mathrm{R}_{ft} = \alpha_j + \beta_j(R_{mt} - \mathrm{R}_{ft}) + s_j SMB_t + h_j HML_t + \varepsilon_i \qquad (3.2.2)$$

$$\mathrm{R}_{ISt} - \mathrm{R}_{ft} = \alpha_c + \beta_c(R_{mt} - \mathrm{R}_{ft}) + s_c SMB_t + h_c HML_t + w_c WML_t + \varepsilon_i \qquad (3.2.3)$$

The data concerning the risk factors just presented was collected at Kenneth R. French website[2], which provided monthly data related to the European market.

In order to complete this analysis, some investment strategies will be tested using the quantile portfolios previously constructed. Therefore, to test the profitability of strategies relying on Recognition Heuristic philosophy, it will be bought the portfolio with the highest increment on search volume, as this variable is intended to function as proxy of investor’s recognition. Additionally, a more aggressive strategy will be employed, where the portfolio with the highest increment on search volume will also be bought and it will be shorted the portfolio from which the search volume most decreased (zero-investment strategy).

As the first two months of data are necessary to compute the change in Google Trends variable, then the investor will receive the return of the following month, i.e the third month, the time period where returns will be analysed spans from March 2004 to April 2015.

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[2] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

4. Analysis of results

In this chapter it will be discussed this dissertation results based on the authors findings and studies.

All the information here presented is the result of the several methodologies adopted and already discussed earlier.

4.1. Survey

The survey was performed during December 2014 and intended to infer which stocks from the index STOXX® Europe 50 were most recognized by the participants.

During this period it was possible to collect the answers from 272 participants. As per Table 4.1.1, it is possible to observe that mostly of the participants are Portuguese (91.55%), followed by Vietnamese (2.94%) and Indian (1.10%). These results show that the broader majority of the participants have some proximity to the authors from this study. In fact, most of the participants that were requested to contribute to this study are mostly from University of Porto. It is also important to highlight that more than half of the participants have between 18 and 25 years old and slightly more than 96% have 40 years old or less. More detailed information regarding the participant's group age may be found on Table 4.1.2.

Table 4.1.1 Participant's nationality

Nationality	Percentage
Portuguese	91.55
Vietnamese	2.94
Indian	1.10
Others	4.41

Source: Survey by authors

Table 4.1.2 Participant's group age

Group age	Percentage
<18	0.73
18 – 25	57.72
26 – 30	26.84
31-41	11.03
41 – 50	2.21
>50	1.47

Source: Survey by authors

Regarding the company names identified by each individual, it is possible to infer that on average a total of 21 companies were identified by participant. Additionally, only 3.31% of the participants were able to recognize 40 or more company names. From the opposite side, 8.82% of the individuals that contributed to the survey recognized less than 10 companies. More information regarding the number of companies identified is disclosed on Table 4.1.3.

Table 4.1.3 Number of company names identified

Number of companies identified	Percentage
0 – 9	8.82
10 – 19	37.13
20 – 29	35.29
30 – 39	15.44
40 – 50	3.31

** On average each participant identified 21 companies.*
Source: Survey by authors

As mentioned on the previous chapter, the companies recognized by more than 90% of the participants were chosen to be part of the Highly Recognized portfolio. On the other hand, the company names recognized by less than 10% were also selected for the

Unrecognized portfolio. At Table 4.1.4 and Table 4.1.5 it is possible to observe the composition of both portfolios built on 5th January, which were liquidated on 5th June, after holding them for five months without performing any reallocation.

Table 4.1.4 Highly Recognized portfolio

Company	**Participants that identified the company name**	
	Number	**Percentage**
Barclays	264	97.1
Nestle	259	95.2
Banco Santander	255	93.8
Siemens	254	93.4
Vodafone	249	91.5
Deutsche Bank	247	90.8
Axa	246	90.4

Source: From authors

Table 4.1.5 Unrecognized portfolio

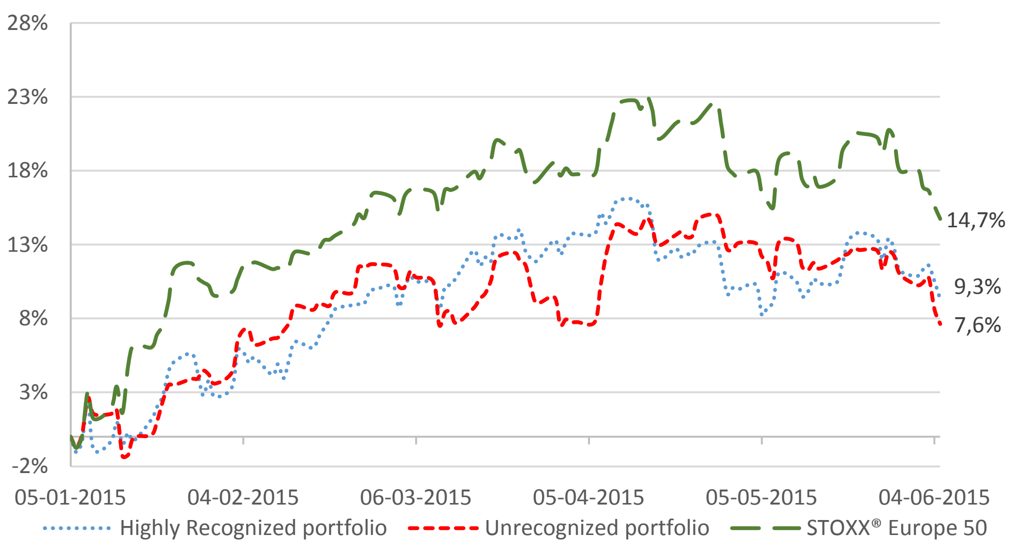
Company	**Participants that identified the company name**	
	Number	**Percentage**
Bae Systems	27	9.9%
Reckitt Benckiser	26	9.6%
Lvmh Moet Hennessy	25	9.2%
BHP Billiton	23	8.5%
National Grid	20	7.4%
Cie Financiere Richemont	15	5.5%
Glencore PLC	15	5.5%
BG GRP	14	5.1%
BT GRP	12	4.4%
Anheuser-Busch Inbev	11	4.0%
Astrazeneca	0	0.0%

Source: From authors

Before analysing the returns provided by each portfolio, it is important to mention that all the rates of return presented below were calculated excluding the transaction costs. Therefore, all the cost associated with building, maintaining and liquidating the portfolios are not being considered to this dissertation.

The Figure 4.1.1 represents the cumulative average returns for the three portfolios under analysis: the Highly Recognized, the Unrecognized and the Market portfolio, here represented by the performance of STOXX® Europe 50 index. At a glance, it is possible to verify that the market portfolio was the one which yielded the greatest return, 14.7% from January until June. The least profitable portfolio was the Unrecognized portfolio, where the return of 8.44% was slightly below from the Highly Recognized portfolio (9.3%).

Figure 4.1.1 Portfolio Cumulative average return



Source: From authors

Nonetheless, it should also be discussed the risk factors inherent to each investment strategy. In other words, it must be accessed the risk that investors incur when they are exposed to the different investment strategies. In this sense, within Table 4.1.6 it is observable the returns already discussed and, additionally, the standard deviation and each portfolio Beta. These two indicators provide a measurement of risk, which it will be useful to infer if the returns obtained are appropriate for the risk taken.

Accordingly to Table 4.1.6, the daily standard deviation for the Highly Recognized portfolio (0.99%) and for the Unrecognized portfolio (0.93%) are very similar to the market standard deviation (0.95%). Furthermore, by analysing the portfolio Betas, it is possible to conclude that both the Highly Recognized portfolio as well the Unrecognized portfolio are well succeed replicating the market price movements presenting a Beta equal to 1.05 and 1.01, respectively.

Therefore, it is possible to infer that all the three portfolios presents an almost equal level of risk and, in consequence, the level of return provided by each portfolio really distinguishes that the market portfolio is, by far, the most profitable portfolio.

Table 4.1.6 Portfolio's return and risk characteristics

Portfolio	Cumulative Average Return	Daily Average Return	Daily Standard Deviation	Beta[3]
Highly Recognized	9.29%	0.09%	0.99%	1.05
Unrecognized	7.63%	0.08%	0.93%	1.01
Market	14.74%	0.13%	0.95%	1.00

Source: From authors

In a nutshell, during the period considered for this analysis the best strategy was to hold the Market portfolio, however the Highly Recognized portfolio still yielded better returns than the Unrecognized portfolio. Please bear in mind that the results do not account for any transaction costs. For instance, constructing a portfolio with several stocks may be more expensive than buying the market portfolio, through an ETF for instance. In either case, the return obtained by the market more than justifies the selection of this investment strategy.

[3] The portfolio Beta was calculated as the average Beta for each stock composing the portfolio. Data was collected from Thomson Reuters Datastream for the time period of 05/01/2015.

The results here obtained contrast to Borges *et al.* (1999), which also experienced an extremely bull market and the Recognition Heuristic portfolio yielded better returns than the market portfolio. In opposite, the results here obtained fit the findings from Andersson and Rakow (2007), which concluded that Recognition Heuristic has no special advantage over sophisticated knowledge neither over the market.

Recalling Pachur *et al.* (2011, p. 4) "collective recognition has been found to be correlated with environmental quantities such as stock profitability (…) nevertheless, these tests are not direct implementations of the recognition heuristic, which models the use of individual recognition".

Here it is possible to adopt a different approach from the previous studies and infer if each participant would yield better returns if investing in the companies he recognizes and the level of "ignorance" he possesses. Therefore, for each participant in this survey it was constructed a portfolio with the stocks that the participant recognized. The portfolio return was also computed using the holding period from 5th January until 5th June. The portfolio was equally weighted for each stock.

The main goal of this study was to check if investors with lower knowledge in financial markets (that identified fewer companies) would yield better returns than investors that have a broader knowledge on this field (identifying most of the companies).

Moreover, each participant was ranked accordingly to its stock market experience. In order to access the experience from each participant the data obtained for education level, the frequency that each participant read financial news and the frequency that they invest in the financial markets were taken.

Nonetheless, the information collected is categorical, so it is necessary to transform it into numerical, in order to be possible to infer if more experienced participants yield less or more returns that less experienced ones. To do that, it was created an experience matrix which attributed points to the answers for each question, in order to rank the participant. The overall experience level is obtained by summing the experience points obtained for each three questions.

At this stage, it is possible to infer if the portfolio return (r) depends on the number of companies identified (CI) and in the experience rank (ER) for each investor, using the following equation:

$$r_i = \alpha_i + \beta_1 CI_i + \beta_2 ER_i \tag{4.1.1}$$

Recurring to statistical software Eviews 8, it is possible to estimate the equation above through the OLS (Ordinary Least Squares) Regression Model.

Table 4.1.7 Company recognition and experience rank effect on portfolio's return

Parameter	Coefficient/Value	Std. Error
α	0.090796***	0.002166
$Companies\ identified$	0.000892***	0.000111
$Experience\ Rank$	-0.000222*	0.000134
R^2	0.222132	
F-statistic	38.40854***	

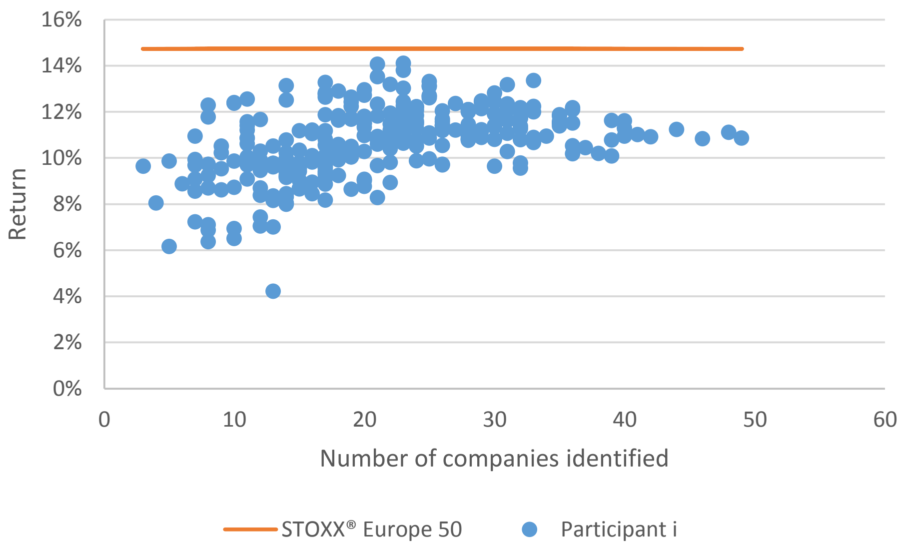
*Source: From authors. Significant level at 1 percent level - ***; significant at 5 percent level - **; Significant at 10 percent level - *.*

The R^2 for this model is 0.222132, which means that approximately 22.2% of the model variability can be explained by the variables included in this analysis. Moreover, the model is statistically significant with an F-statistic of 38.40854, which represents a p-value of 0.000.

Individually, the variable *companies identified* is statistically relevant for this model for a significance level lower than 1%. Nonetheless, the relationship between this variable is positive with the portfolio return. In fact, for each additional stock identified the investor is expected to yield additional 0.0892% return. This finding is contrarian with the feature "less is more" from the Recognition Heuristic.

Regarding the *experience rank* the effect that produces in the portfolio return is the expected for Recognition Heuristic philosophy, which dictates that less experienced investors will yield higher returns. In fact, each additional experience point earned decreases the portfolio return by 0.0222%.

Figure 4.1.2 Portfolio returns for each participant compared with the STOXX® Europe 50



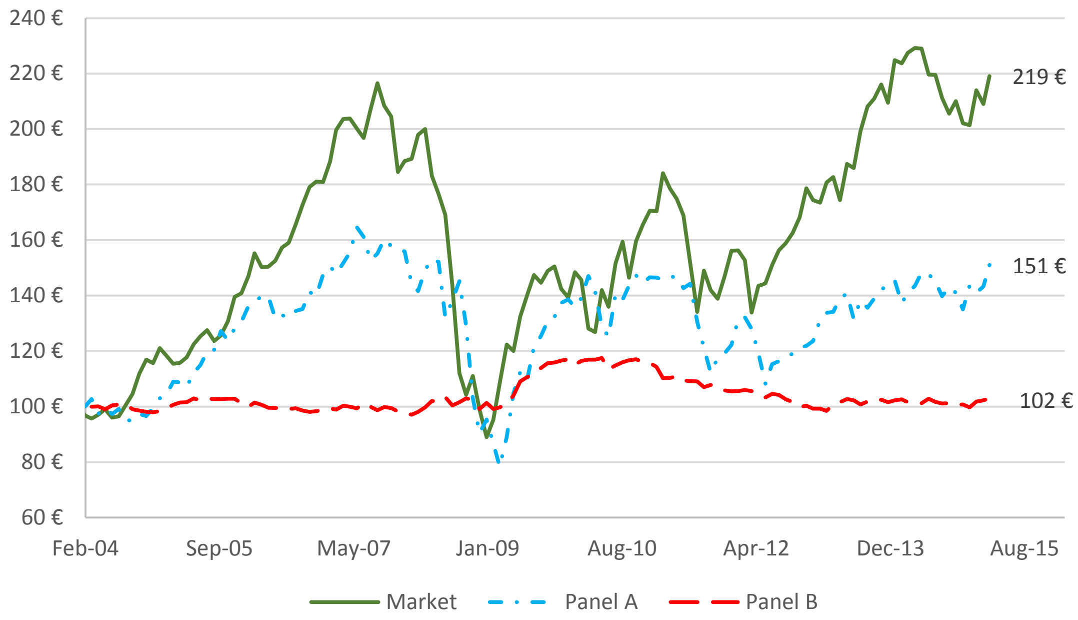
Source: From authors.

From Figure 4.1.2 it is possible to conclude that not only a single participant was able to beat the return from the Market portfolio for the same period, here represented by the STOXX® Europe 50 index. Assuming the Efficient Market Hypothesis (EMH) from Fama (1970), it would be expected that about half of the participants would be able to beat the market portfolio, even if it was only by chance.

4.2. Google Trends as proxy for investor's recognition

This chapter intends to discuss if the data freely provided by Google Trends may be useful for investors when deciding in which stocks they should invest. The search volume functions as proxy of investor's recognition, where increments of this variable should also denote higher company recognition. Consequently, as per discussed in the methodology, two investment strategies will be employed to test if relying on the Recognition Heuristic principles is possible to yield abnormal returns in the European stock market.

Figure 4.2.1 Return on a 100€ investment from February 2004 until April 2015.



Source: From authors.

In Figure 4.2.1 it is possible to observe the performance of 100€ investment from February 2004 until April 2015 in three different strategies: investing in the market portfolio, Panel A, that represents the strategy of buying the stocks that had the most increase in search volume each month and Panel B, which is an extension of the previous panel by also shorting the stocks where the search volume decreased the most. Please note that no transaction costs and currency effects were taken into consideration. As per Figure 4.2.1 it is possible to infer that the Market strategy was the most profitable during the entire period. In fact, the investor that followed this strategy had more money value during almost every month, from the period under analysis.

The Panel A, which is the conservative strategy adopted following the Recognition Heuristic principles, was the second strategy most profitable. Additionally, it can be graphically observed that this strategy managed to replicate the market with less volatility.

The performance of the most aggressive strategy employed, Panel B, was mostly flat during the entire period. In fact, a 100€ investment in this strategy on February 2004 only worth 102€ in August 2015, more than 10 years later. The principal reason for this performance is that both portfolios contained in this investment performed very similarly during the entire period, where the gains of the portfolio held were cancelled by shorting the other portfolio.

In order to depict the risk-adjusted performance, these strategies were regressed with the market models CAPM from Sharpe (1964), the three-factor model from Fama and French (1993) and the Carhart (1997) four-factor model. The estimation of Jensen's α helps to determine if an investment strategy is earning the proper return for its level of risk. Therefore, a positive α reflects the earning of excess of return by the investment strategy, which ultimately means that the market was beaten.

In Table 4.2.1 it may be observed the regressed coefficients for each strategy in the described market models.

From Panel A, that represents the investment strategy that follows the Recognition Heuristic principles in a conservative approach, which buys the portfolio with greatest increment in search volume, it is possible to observe that the Jensen's α are positive in the three models. This may evidence that this strategy was able to beat the market during the period under analysis. For instance, the CAPM and FF Three-factor intercept is 0.002, which represents a 0.2% excess return per month, over the market performance. In the C Four-factor model, the Jensen's α increases to 0.3% per month.

These results are very optimistic for the strategy that follows the Recognition Heuristic philosophy as it demonstrates that it is possible to consistently yield abnormal returns by following this strategy. Unfortunately, in the three models the variable is statistically insignificant for every significant level equal or lower than 10 percent. Therefore, the Jensen's α is not statistically different from 0. As a consequence, Jensen α's are not considerable enough positive to infer that Recognition Heuristic may lead to excess returns in the European stock market.

*Table 4.2.1 Trading profits related to Google Search volume. This table depicts the profitability of trading strategies described on Panel A, B and C. Standard errors are provided in parentheses. Number of observations: 134. Significant level at 1 percent level - ***; significant at 5 percent level - **; Significant at 10 percent level - *.*

	CAPM	**FF Three-Factor**	**C Four-Factor**
Panel A: Buy the portfolio with highest increment in search volume.			
Intercept ($Jensen's\ \alpha$)	0.002 (0.004)	0.002 (0.004)	0.003 (0.004)
$R_{mt} - R_{ft}$	0.187** (0.077)	0.0154* (0.090)	0.128 (0.091)
SMB_t	-	0.930*** (0.224)	0.915*** (0.223)
HML_t	-	0.125 (0.233)	0.005 (0.245)
WML_t	-	-	-0.187 (0.124)
R^2	0.042	0.155	0.170
F-statistic	5.832**	7.965***	6.606***
Panel B: Buy the portfolio with highest increment in search volume and sell portfolio from which the search volume most decreased.			
Intercept ($Jensen's\ \alpha$)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.001)
$R_{mt} - R_{ft}$	0.055*** (0.019)	0.048** (0.023)	0.037 (0.023)
SMB_t	-	0.031 (0.058)	-0.024 (0.057)
HML_t	-	0.033 (0.061)	-0.020 (0.063)
WML_t	-	-	-0.082** (0.0316)
R^2	0.061	0.065	0.112
F-statistic	8.611***	3.020**	4.057***

Source From authors. Eviews 8.

The investment strategy β for the CAPM model is 0.187, which means that investment strategy followed in Panel A is a lot less risky than the market. Therefore, any attempt to compare solely the average returns on this strategy on a market index without explicit adjustment for differential riskiness would be highly biased against the funds.

Regarding the Panel B, that represent a more aggressive variant of the Recognition Heuristic principles, which is to buy the stocks that increased the most in search volume on the previous month and short the stocks where the search volume mostly decreased, the Jensen α's are negative for the CAPM and the FF Three-factor model and 0.000 for the C Four-factor model. This would mean that this strategy yields less 0.01% than the market appropriate return each month, following the CAPM and the FF Three-factor model and would yield exactly the appropriate return (given the market as benchmark) each month, as per the C Four-factor model. Nevertheless, all the three Jensen α's are statistically insignificant for a significance level equal or lower than 10%. Therefore, these α's are not statistically different from 0, which means that the Panel B strategy is not capable of beating the market consistently, considering a confidence level of 90%.

During the period under analysis it was experienced a rising market, where strategies relying on Recognition Heuristic philosophy should yield the better returns for its investors (Borges *et al.*, 1999; Boyd, 2001). Nevertheless, the results here obtained provide weak signs that investment strategies based on Recognition Heuristic may yield abnormal returns as per Borges *et al.* (1999). Additionally, it is necessary to assume that no transaction costs were accounted on this study. In fact, the investment strategy here presented requires portfolio adjustments on a monthly basis in order to keep the most searched companies in the portfolio. Therefore, it would be wise to assume that passively investing in the market would be more profitable than following the investment strategy proposed earlier, as per the results obtained.

5. Conclusions

The main objective of this master dissertation is to study the impact of Recognition Heuristics in the financial markets. Many authors have already studied this heuristic when applied to financial markets, nonetheless there is lack of consensus within the literature.

Borges *et al.* (1999) were the first authors to analyse this phenomena and concluded that following an investment strategy based on recognition heuristics would yield higher returns than passively invest in the market. Later, Boyd (2001) tried to replicate Borges *et al.* (1999) findings and concluded that Recognition Heuristics may yield abnormal returns only in bullish markets. Finally, Andersson and Rakow (2007) followed the same methodology as prior studies and concluded that investor's "ignorance" would not be a valuable asset when taking investment decisions, nevertheless Recognition Heuristics strategies would yield better returns in bear markets than in rising ones.

This master dissertation contributes to the broader the knowledge available in this field and contributes to the discussion of Recognition Heuristics when applied to financial markets, as until now it is obvious the lack of consensus on the topic. Moreover, the three existing studies from the authors referred above were mainly applied to U.S and German markets, apart from Andersson and Rakow (2007) that extended their analysis to few other European economies. In this sense, it was valuable to study the Recognition Heuristic in the European market as a whole in order to infer the profitability of investment strategies relate to this heuristic.

In order to proceed with this study, two different approaches were undertaken. The first method replicated the methodology adopted from previous studies already discussed. All the three studies used the same method to estimate the existence of Recognition Heuristics in the financial markets and it was also used in this master dissertation. The second method was more innovative and intended to take advantage of new sources of data available to study if the fast and frugal Recognition Heuristic may also be applied to financial markets.

The first method adopted was a survey performed in order to understand which companies are the most recognized by the participants. Therefore, two portfolios were constructed, one composing the highly recognized companies and other with the less recognized companies. The returns were then compared with the market.

The second method from this master dissertation intended to take advantage of Google Trends. Monthly internet search volume data was collected and used statistical software to infer the impact of changes in search volume on future stock return. In order to do that, three equal sized portfolios were constructed each month: one with the companies with that mostly increased in search volume, another with the companies that mostly decreased in search volume and the last with the companies which verified small changes in search volume. Then, two investment strategies were developed based on the Recognition Heuristic principles and the returns for those strategies were regressed using the most relevant market models: the CAPM from Sharpe (1964), the Three-factor model from Fama and French (1993) and the Carhart (1997) Four-factor model. The Jensen's alpha was estimated to infer if the designed investment strategies could beat the market on a consistent basis.

From the first method, it was possible to conclude that the market portfolio performed much better than the recognized portfolio during the period from 5th January until 5th May (yielding 14.7% against 9.29%), which by its turn beat the unrecognized portfolio (8.4%) by a tinny margin. Moreover, it matters to mention that all three portfolios presented similar levels of risk, measured by the daily standard deviation and the portfolio beta. This finding was not expected by the prior studies that claim that Recognition Heuristics strategies yield great returns during bullish periods (Borges *et al.*, 1999). Moreover, it was intended to check the "individual recognition", where several portfolios were constructed, one for each participant containing the companies identified. It was found that the most successful participants were the ones that recognized more companies, contradicting the "less is more" effect from the Recognition Heuristic.

Regarding the Google Trends study, the results indicated that the strategy based on the Recognition Heuristic principles yielded weak, but statistically insignificant abnormal returns on a consistent basis. Nevertheless, the investment strategy would imply to modify the portfolio on a monthly basis, which can lead to high transaction costs that could absorb the strategy profitability. Therefore, it is possible to conclude that following the investment strategy based on Recognition Heuristic principles would not produce better returns to investors than investing in the market portfolio.

Through the exhaustive analysis performed about the Recognition Heuristic in the European stock market it is possible to conclude that no evidence was found about the viability on exploring these type of strategies. In fact, the investors would always yield better returns when adopting a passive strategy of investing in the market.

Therefore, it would be wise to assume that the European market presents at least a degree of efficiency where no investor would yield abnormal returns following the Recognition Heuristic.

The market conditions that Borges *et al.* (1999) and Boyd (2001) faced on their studies, combined with the short time period under analysis were the major limitations to their findings. These limitations are a natural barrier to the survey methodology adopted, as it only allows observing the performance of portfolios in the few following months. In order to overcome these limitations incurred by previous authors, it was developed the methodology regarding the Internet search volume, through Google Trends. In fact, being able to analyse 10 years of data enabled us to face different market conditions and test the profitability of Recognition Heuristic strategies on a general and broader approach.

Despite of the results here accomplished being useful to understand the performance of Recognition Heuristic strategies over a comprehensive time horizon, it would be interesting to depict its viability during the different market conditions faced. This analysis could provide additional information about the preferable scenario to employ our strategies and, ultimately, enhance the profitability of Recognition Heuristic.

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